ECG Disease Classification Using Graph Convolution Networks

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Problem Statement

- We are given annotated ECG data, i.e. ECG recordings along with the corresponding disease.
- Given a new ECG sample, we want to clasify into the different categories of disease.
- In current framework, only considered one-label classification, not multi-labeling.
- Previous work can be classified into two categories:
  - Signal Processing techniques for good feature extraction (eg. QRS peak detection) coupled with standard Machine Learning approaches.
  - Neural Networks for extraction of feature as well as for classification (eg. Convolutional Networks as there is periodicity associated)
- We want to extend the success of Neural Networks to this task as well.

Heart diseases considered

The following heart diseases are considered:

- Myocardial Infarction
- Cardiomyopathy Heart failure
- Bundle branch block
- Dysrhythmia
- Myocarditis

Dataset

The dataset used for experiments is the PTB databas from Physionet repository.

- Consists of 15 channels (12 for conventional ecgs, 3 frank leads).
- Resolution is 16bit and sampling rate is 1kHz.
- Total 549 recordings from 290 subjects. 148 are diagnosed with Myocardial Infarction (MI).
- We use parts of each classification for training and rest for testing.

CNN on ECG

A simple Convolutional Network is tested on ECG.

- Architecture adopted is 1D version of the LeNet architecture. The network is :

$$conv- > maxpool- > conv- > maxpool- > fc- > fc- > softmax$$

- Base implementation results in accuracy around 80-87%.
- On top of each convolution layer, we add a batch normalization.
- This gives accuracy boost upto 93%-94%
- State of the Art to the best of knowledge is 96%
- It is also noted that using more number of channels doesn't lead to increase in the accuracy.

Exploiting Data from Different Channels

- We note that the ECG leads are put at particular locations. We would like to be able to use the underlying spatial distribution as well and incorporate data from the different leads. This is something that the standard CNN can not do.
- For this reason we go to Graph Convolutional Networks. This can be viewed as a generalization of CNN to non-euclidean spaces.
- It is not trivial to generalize CNN to non-euclidean spaces.

Graph CNN (Optional)

Two main approaches to Graph CNN

- Spectral Approach [ChebNet, NIPS2016]
- Spatial Approach [MoNet, CVPR2017]